THE JOURNAL OF
impact&esg
INVESTING

PORTFOLIO
MANAGEMENT
RESEARCH

volume 1
issue 1

JESG.pm-research.com

fall
2020

# Combining E, S, and G Scores: *An Exploration of Alternative Weighting Schemes*

LINDA-ELING LEE, GUIDO GIESE, AND ZOLTÁN NAGY

MSCI

### Linda-Eling Lee

*Managing Director and Global Head of ESG Research*

As Global Head of Research for MSCI's ESG Research group, Linda-Eling Lee oversees all ESG-related content and methodology. MSCI ESG Research is the largest provider of ESG Ratings and analytics to global institutional investors. Linda leads one of the largest teams of research analysts in the world who are dedicated to identifying risks and opportunities arising from significant ESG issues.

Linda joined MSCI in 2010 following the acquisition of RiskMetrics, where she led ESG ratings research and was head of consumer sector analysis. Linda joined RiskMetrics Group in 2009 through the acquisition of Innovest. Prior to joining Innovest, Linda was the Research Director at the Center for Research on Corporate Performance, developing academic research at Harvard Business School into management tools to drive long-term corporate performance. Previously, she was a strategy consultant with Monitor Group in Europe and in Asia.

Linda received her AB from Harvard, MSt from Oxford, and PhD in Organizational Behavior from Harvard University.

She has published research both in management journals such as the Harvard Business Review and MIT's Sloan Management Review, as well as in top academic peer-reviewed journals.

### Guido Giese

*Executive Director, Core Equity Research*

Guido Giese is an Executive Director in MSCI's Core Equity Research team, where he is responsible for applied research and thought leadership in key areas such as ESG integration, impact investing, and factor investing.

Prior to joining MSCI, Guido was responsible for the sustainability index solutions business at RobecoSAM, following his tenure as Head of Research and Development at index provider STOXX Ltd, where he was responsible for developing new index solutions. He has more than 20 years' experience in research and product development in the asset management industry.

Guido holds a PhD in Applied Mathematics from the Swiss Federal Institute of Technology Zurich and has authored numerous articles in international journals for quantitative finance and risk management.

### Zoltán Nagy

*Executive Director, Core Equity Research*

Zoltán Nagy is an executive director in MSCI's Equity Core Research team. In this role, he focuses on questions related to the integration of factors and ESG into the equity portfolio management process. Zoltán joined MSCI in 2008, and first worked on the development of new index methodologies and on other index-related research.

Prior to entering finance, he was a post-doctoral researcher at the University of Algarve, Faro, Portugal. His area of research was quantum integrable systems.

Zoltán holds a PhD degree in Theoretical Physics from the University of Cergy-Pontoise, France, and an engineering degree from the Ecole Polytechnique, France. He is also a CFA® charter holder.

# Combining E, S, and G Scores: *An Exploration of Alternative Weighting Schemes*

**Linda-Eling Lee, Guido Giese, and Zoltán Nagy**

**Linda-Eling Lee**
is a managing director, and the Global Head of ESG Research, at MSCI in New York, NY.
**lindaeling.lee@msci.com**

**Guido Giese**
is an executive director in Equity Core Research at MSCI in London, UK.
**guido.giese@msci.com**

**Zoltán Nagy**
is an executive director in Equity Core Research at MSCI in Budapest, Hungary.
**zoltan.nagy@msci.com**

**KEY FINDINGS**

- Environmental (E), social (S), and governance (G) scores have shown different relationships with financial characteristics of firms. Historically, governance has provided the strongest significance, social the weakest.
- A combination of E, S, and G scores that maximized historical financial significance did not lead to a signal with superior long-term stock-price effect.
- The weighting of E, S, and G issues in aggregating a composite score may better reflect the dynamically changing ESG landscape, aiming to capture unfolding, emerging risks.

**ABSTRACT:** *How an overall rating is constructed can have a significant impact on its usefulness to investors. In this study, we tested two approaches: equal weighting and backward optimization. Equally weighting E, S, and G pillar scores across sectors showed less financial significance than the stand-alone G pillar score—that is, without E and S scores—over the 13-year study period. Although backward optimization showed greater significance than the stand-alone G scores, this approach may underestimate the importance of ESG indicators to financial results over longer periods of time. These results suggest that investors seeking to combine E, S, and G into an aggregate ESG score should proceed with caution. A naïve approach such as equal weighting could introduce noise that decreases financial significance and a backward-optimized approach may ignore the importance of different time frames in how ESG risks unfold. Our findings illustrate the historical value in prospectively adjusting the selection and weighting of ESG Key Issues industry by industry to capture companies' exposure to dynamic and emerging risks.*

**TOPIC:** ***ESG investing****

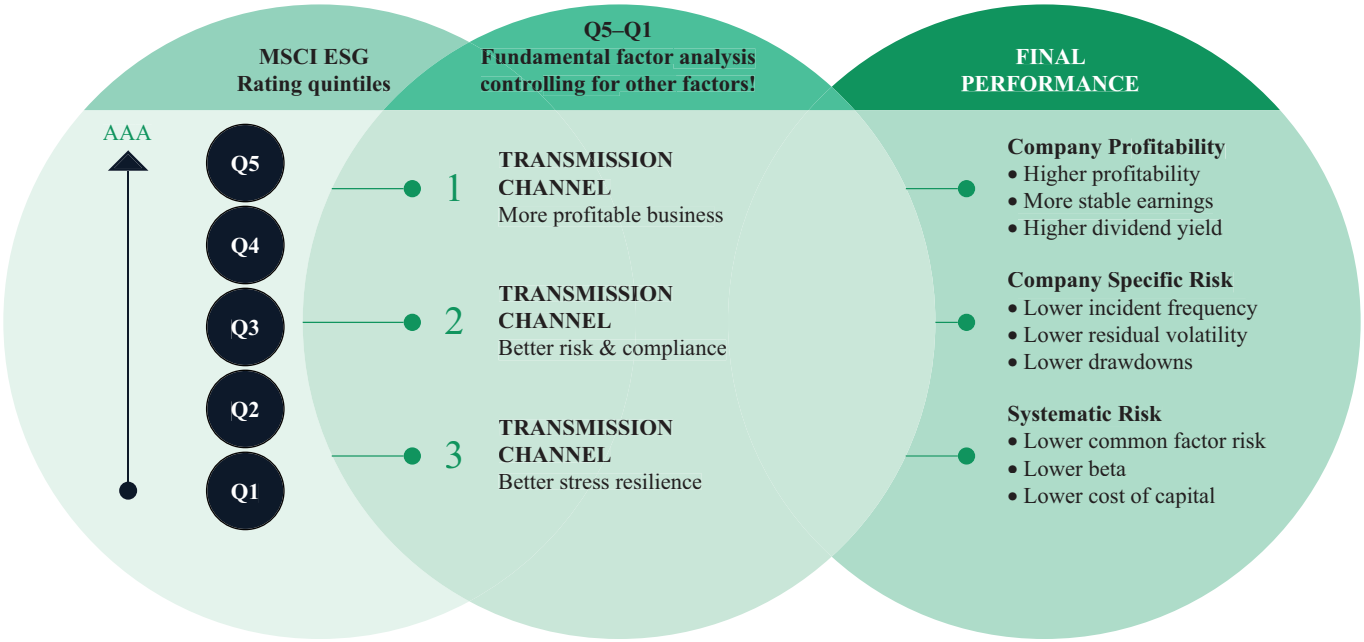
*All articles are now categorized by topics and subtopics. **View at PM-Research.com.**

There are many ways to construct a company ESG score, involving different mixtures of financial and nonfinancial inputs. Investors often have different objectives for an ESG score, from aligning with personal values to capturing financially significant risks and opportunities. Practitioners aiming to improve financial outcomes face the challenge of determining the most influential criteria for firm performance and the best way to combine different ESG issues into an aggregate ESG score or rating.[1] Understanding the financial significance of ESG

[1] ESG scores are used in the construction of ESG ratings.

## EXHIBIT 1

**Economic-Transmission Channels to Be Tested**




*Source: MSCI ESG Research LLC.*

ratings is not only important for investors using proprietary or third-party ESG ratings in portfolio construction (which has been the main perspective of most previous studies), but also to address the question of how ESG ratings may be improved.

In this article, we first established how companies' ESG characteristics (measured by using MSCI's E, S, and G pillar scores, which underlie the ESG rating) are associated with financial risk and return. Then we compared how different hypothetical approaches to combining E, S, and G pillar scores into an aggregated ESG rating maximize financial performance.

## ECONOMIC-TRANSMISSION CHANNELS

To establish how companies' ESG characteristics are associated with financial risk and return, we built on previous research in which we identified three economic-transmission channels—the cash-flow, idiosyncratic-risk, and valuation channels—through which ESG information translates into financial risk and performance (Giese et al. 2019a). These channels can be summarized as follows (see schematic in Exhibit 1):

- Cash-flow channel: Companies with high ESG ratings on average have historically been more profitable, displayed more stable earnings, and paid higher dividend yields after controlling for size bias. The economic rationale suggests that stronger ESG characteristics may have been linked to better business practices, which may result in attracting more talented employees and better innovation management, developing long-term business plans and incentive plans for management, and achieving better customer satisfaction (Fatemi et al. 2015).
- Idiosyncratic-risk channel: Companies with high ESG ratings have historically shown less frequent drawdowns, controlling for size and industry (Giese et al 2019a). Companies with high ESG ratings were considered to have had better abilities to manage and mitigate company-specific risks than lower-ranked peers in the same sector.
- Valuation channel: Companies with high ESG ratings have historically shown lower levels of systematic risk, lower costs of capital, and, therefore, higher levels of valuation. For example, the authors have shown lower levels of volatility for high-rated

companies in MSCI's Barra Global Total Market Equity Model for Long-Term Investors (GEMLT) while controlling for size. In addition, some MSCI ESG indexes using ESG ratings inputs have shown lower drawdowns than their market-capitalization-weighted parent indexes in market crisis situations (Giese et al. 2019b; Lodh 2020). The economic rationale is intuitive: Companies with strong ESG characteristics may have been more resilient when faced with changing market environments, such as fluctuations in financial markets and changes in regulation. Researchers have found that companies with stronger ESG characteristics have experienced less exposure to risks and higher levels of valuation.[2]

We found evidence supporting these transmission channels, controlling for companies' market capitalization and industry within the MSCI ACWI World Index.

This model shows at a high level how ESG information has been conveyed. ESG ratings, which are built on ESG scores, reflect this information. To increase our understanding of how ratings are constructed, we also examined the financial significance of these transmission channels at the level of the individual E, S, and G pillar scores.

To do this analysis, we calculated the exposure to financial variables across five size-adjusted pillar-score quintiles (Q1 to Q5), which were rebalanced monthly, with Q1 indicating the companies with the lowest pillar score and Q5 the companies with the highest pillar score.[3] We used size-adjusted quintiles to ensure potential financial differences were not due to differences in size.[4]

Using this quintile-level aggregate exposure data, we examined how each of the economic-transmission channels performed for the aggregate MSCI ESG scores, as well as for its constituent components—the E, S, and G pillar scores. We compared the Q5-Q1 quintile differences for the financial variables transformed to z-score format in each economic-transmission channel (Exhibit 2).

In line with Giese et al. (2019a), the highest-rated quintile on the aggregate MSCI ESG score showed higher levels of profitability, lower levels of idiosyncratic risk, and lower levels of systematic risk across all three pillars.

The E, S, and G pillar analysis in Exhibit 2 shows that the G score was the most significant and the S score was the weakest.

## THE ROLE OF WEIGHTS IN CREATING AN ESG SCORE

The ESG rating (and corresponding ESG score) used in our analysis[5] is based on an industry-specific selection of 37 key ESG risks (called Key Issues), as well as an industry-specific weighting of those issues. To what extent has the weighting scheme contributed to the findings that the overall ESG rating and E, S, and G pillar scores have shown financial significance? And to what extent can alternative weighting schemes improve the financial relevance of an ESG rating? We tested two approaches: backward optimization and simple equal weighting.

In the first approach, one can use quantitative analysis to determine the weighting scheme of an ESG-rating model, seeking to improve the strength of financial relevance based on historical evidence. On the one hand, quantitative analysis uses data to identify ESG indicators that have shown strong financial significance historically and remove or minimize less relevant indicators.

On the other hand, relying on historical data runs the risk of data mining: Although these indicators may have worked in the past, they may not deliver similar results in the future. This may be especially true with ESG data, as ESG risks have been more dynamic and evolving than risks quantified by traditional metrics such as style factors. For example, extreme weather events and

[2] For example, see Eccles et al. (2014), El Ghoul et al. (2011), and Gregory et al. (2014).

[3] In the MSCI ESG Rating model, a higher MSCI industry-adjusted ESG score represents better ESG characteristics. Financial variables, such as beta or gross profitability, are based on GEMLT and are, therefore, in the format of *z*-scores, which are normalized values, calculated by first subtracting the cross-sectional mean from all values and then dividing the difference by the cross-sectional standard deviation. *Z*-scores have zero mean and unit standard deviation. Following the GEMLT methodology for risk-related variables, we subtracted cross-sectional global means; for fundamental data-related variables, we subtracted cross-sectional country means to control for potential country biases in fundamental data. Standard deviation was calculated globally.

[4] The size adjustment is achieved by regressing the numerical scores on GEMLT size exposures and an intercept term and keeping the residual as the size-adjusted score.

[5] For an explanation of the methodology used to create the scores, please see MSCI ESG Research (2019).

## EXHIBIT 2
**Exposure Analysis of MSCI ESG Scores, Including Pillar Breakdown**

| Transmission Channel | | Expected Sign Q5–Q1 | Q5–Q1 Exposure Difference: Top-Level Score: MSCI ESG Score | ESG Pillar Breakdown: E z-Score | ESG Pillar Breakdown: S z-Score | ESG Pillar Breakdown: G z-Score |
|---|---|---|---|---|---|---|
| | Gross Profitability | + | 0.13 | 0.05 | 0.06 | 0.24 |
| | Trailing Dividend Yield | + | 0.14 | 0.12 | 0.08 | 0.12 |
| | Residual CAPM Volatility | - | –0.26 | –0.27 | –0.12 | –0.29 |
| | Kurtosis | - | –0.06 | –0.04 | –0.04 | –0.05 |
| | Systematic Volatility | - | –0.23 | –0.20 | –0.09 | –0.33 |
| | Variability in Earnings | - | –0.15 | –0.07 | –0.14 | –0.16 |

*Notes: In the third column from the left, we indicate the sign of Q5–Q1 that was expected based on the transmission channels: We expected a positive sign for profitability and dividend yield and a negative sign for risk-related variables.*

*Source: MSCI ESG Research LLC. Data from December 2006 to December 2019 for the MSCI World Index.*

water scarcity could become more significant in the next two decades. Similarly, consumer concerns and regulatory risk related to privacy protection were very nascent and likely not as significant 10 years ago.

The risk of data mining typically increases with the number of parameters one uses to calibrate a model to a specific dataset. For instance, one could use an optimizer to determine the relative weightings of E, S, and G pillar scores to maximize the statistical reliability of the Q5–Q1 differences in financial variables used. If the optimizer used two values that may vary, and adjusted the weightings annually, that would result in 26 values (or free optimization parameters) for our 13-year study period. Using sector- or industry-specific optimization would multiply the dimensions accordingly. Optimization at the level of a key issue would multiply the number of optimization parameters even more.

Despite these drawbacks, reweighting ESG pillar scores may shed light on how to construct an ESG rating. In addition, we can assess whether such backward optimization might have delivered improvements in financial significance over longer periods.

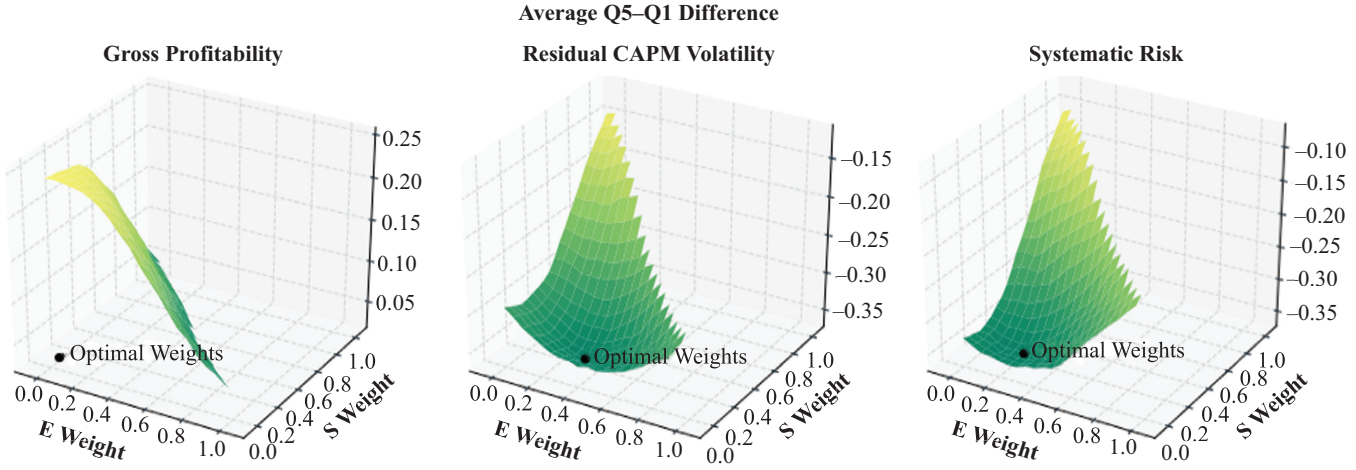
The first question aims to determine what target variable should be used in the optimization. For example, one could backward optimize the weights of E, S, and G within the total ESG score to maximize stock performance within the respective stock universe over the sample period. By construction, this would result in the best possible in-sample financial performance. However, this approach would maximize the risk of data mining and may not lead to robust results, since it would depend on the companies in the sample, as well as the periods used. A more fundamental issue with this approach is that ESG ratings are designed to reflect the financial resilience of companies to long-term environmental, social, and governance risks, and not to predict short-term stock-price correlations.

Therefore, we used fundamental target variables in our optimization. More precisely, we aimed to maximize the effect of combining the pillar scores via the three economic transmisison channels that are shown in Exhibit 2. We selected gross profitability, residual CAPM volatility, and systematic volatility to represent each channel.[6]

Before we implemented the optimization, we examined how the Q5–Q1 differences in the three channels depended on the pillar weights (Exhibit 3). For all three financial characteristics, the largest average Q5–Q1 difference was achieved if the heaviest weighting was given to the governance pillar and the lightest to

[6] As we used a *z*-score format (which creates a standard unit of measurement), we were able to average these three quintile differences in one aggregated target function.

## EXHIBIT 3
**Backward Optimization of ESG Pillar Weights**




*Notes: The charts show on the z-axis the Q5–Q1 differences for profitability, residual volatility, and systematic volatility as a function of pillar weights. Lighter coloring corresponds to more positive values, darker to more negative differences. Data from December 2006 to December 2019 for the MSCI World Index.*

*Source: MSCI ESG Research LLC.*

the social pillar. These results are in line with our earlier observations about the strength of the pillars (Exhibit 2).

For the actual optimization, we then used the average of the Q5–Q1 differences for these three variables as our final target variable, and we sought the pillar weights that yielded an optimally combined ESG score, capturing the largest differentiation in the target variable between the best- and worst-rated stocks.

More concretely, our objective was to maximize the following average difference:

$$\frac{1}{3*T}\sum_{i=1}^{3}\sum_{t=1}^{T} s_i\left(x_{i,t}(Q5) - x_{i,t}(Q1)\right)$$

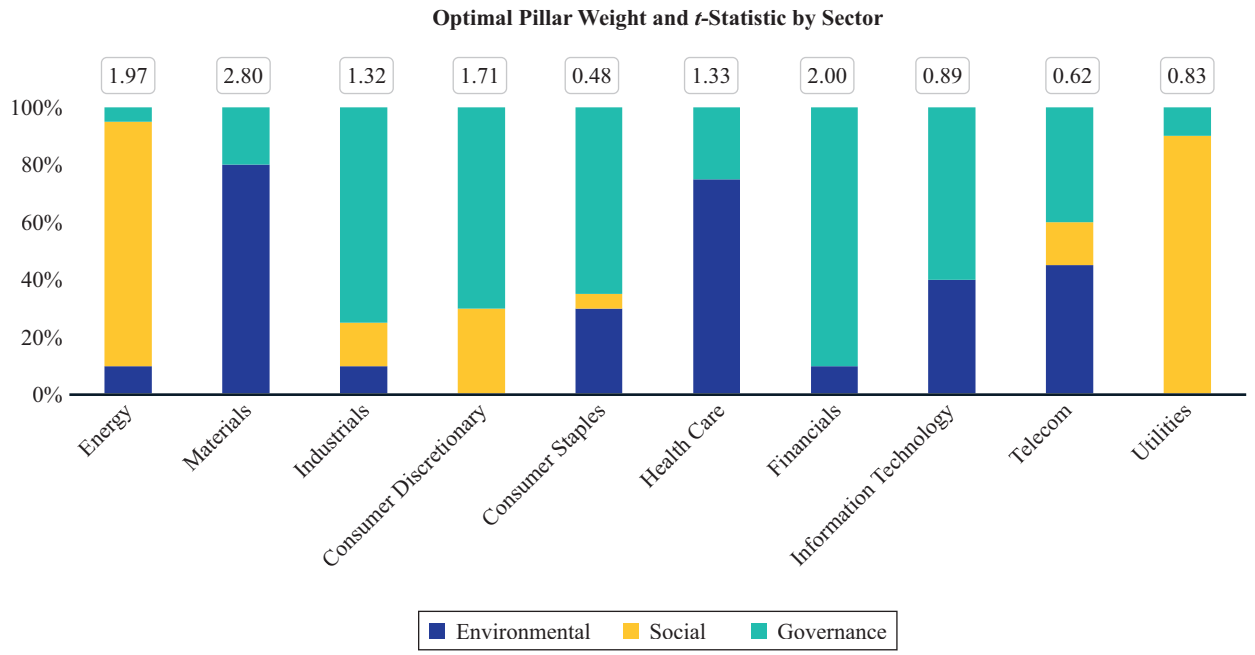
where $x_{i,t}(Qj)$ represents the exposure of quintile $j$ to the variable $i$ at month $t$, and $s_i$ is equal to 1 for gross profitability and equal to −1 for the other variables.

As a simplification, we assumed in all our calculations that pillar weights were constant over time, thereby strongly limiting the number of free parameters. We also picked the combination of E, S, and G weights that maximized the time-series average of Q5–Q1 differences.

As a first step in the optimization, we allowed pillar weights to be sector-dependent. Exhibit 4 shows the results of a sector-specific optimization, where the optimizer chose the relative pillar weights to maximize the average of the Q5–Q1 differences of the three target variables (profitability, idiosyncratic risk, and systematic risk) during the study period. On average, the optimized relative weights were consistent with our previous results showing that the governance pillar had the highest level of significance (a 46% weight on average) and the social pillar the lowest (a 24% weight on average). However, there were significant sectoral differences. In the financial sector, practically all the weight was given to the governance pillar; in the materials sector almost all the weight was given to the environmental pillar.

The large sector-to-sector variation could indicate large differences across sectors. But it could also be a spurious result caused by the larger level of noise in the sector-dependent optimization. To get an indication of the statistical challenges in sector-by-sector optimization, one should consider that sectors contained 1/10th of the total stocks, increasing the confidence bounds by roughly three times. Exhibit 4 also shows that the average *t*-statistic of the optimal sector specific combination exceeded 2.0 for the materials sector only. Therefore, to avoid overfitting to noise, we decided to use the optimal weights that (1) were not sector-dependent and (2) maximized the Q5–Q1 difference in the three-channel average score. This led to 25%, 5%, and 70% weightings for the E, S, and G pillars.

## EXHIBIT 4
**Sector-Specific Optimization of E, S, and G Weights**




*Notes: We omitted the real estate sector because of its short history. T-statistic is calculated as the significance of the difference between Q5 and Q1 exposure to the average of the three variables where quintiles are defined using the sector-specifc combined score.*

*Source: MSCI ESG Research LLC. Data from December 2006 to December 2019 for MSCI World Index.*

Next, we compared the significance of this optimized ESG weighting scheme to equally weighting the three pillars. The results are summarized in Exhibit 5.

We can evaluate the impact of adding E and S key indicators in the three weighting approaches. The optimized approach showed the strongest significance, which was in line with our expectations as the weighting scheme was optimized against the target variables. The equal-weighted approach also showed slightly stronger results than the industry-specific approach of the MSCI ESG score, which used an industry-specific, time-dependent approach to weight the underlying key issues (but not the pillars). This approach resulted, on average, in a higher weight to the S pillar and lower weight to the G pillar than the alternatively weighted approaches.

Although the optimized weights showed the strongest signficance (by design), it may be backward-looking and may underestimate the weights of ESG indicators that may affect financial results over longer periods. What if some ESG indicators were not important in the past but may be more significant in the future?

In fact, an analysis of the actual stock-price performance of these alternatively weighted ESG scores shows that neither the simple equal-weighted approach nor the backward-optimization approach would have correlated to better stock performance or lower levels of volatility during our study period. Rather, as Exhibit 6 shows, the actual overall MSCI ESG scores—constructed using a systematic, prospective recalibration of the key issues and weights in the ESG ratings model—showed a better Q5–Q1 performance difference and a lower level of cyclicality.

What might account for the stronger stock performance over the long term, even as the MSCI ESG score showed weaker significance over the shorter time framce? The much greater granularity and time-varying aspect of the MSCI ESG scores could be a contributing factor. In the weighting scheme, on average, each of the 158 Global Industry Classification Standard (GICS®)[7] subindustries uses six ESG key issues in assigning weights in the MSCI ESG ratings. The selection of key

[7] The Global Industry Classification Standard (GICS®) was jointly developed by MSCI and Standard & Poor's.

## EXHIBIT 5

**Exposure Analysis of Alternatively Weighted ESG Ratings**

| Transmission Channel | | Expected Sign Q5–Q1 | Q5–Q1 Exposure Difference: Existing Top-Level and Pillar Scores: MSCI ESG Score | E z-Score | S z-Score | G z-Score | Alternatively Weighted ESG Scores: Eq Wgt z-Score | Optimized Weights |
|---|---|---|---|---|---|---|---|---|
| | **Gross Profitability** | + | 0.13 | 0.05 | 0.06 | 0.24 | 0.16 | 0.22 |
| | **Trailing Dividend Yield** | + | 0.14 | 0.12 | 0.08 | 0.12 | 0.16 | 0.15 |
| | **Residual CAPM Volatility** | – | –0.26 | –0.27 | –0.12 | –0.29 | –0.32 | –0.34 |
| | **Kurtosis** | – | –0.06 | –0.04 | –0.04 | –0.05 | –0.07 | –0.07 |
| | **Systematic Volatility** | – | –0.23 | –0.20 | –0.09 | –0.33 | –0.27 | –0.33 |
| | **Variability in Earnings** | – | –0.15 | –0.07 | –0.14 | –0.16 | –0.16 | –0.16 |
| | **Average *t*-Statistic** | | 2.41 | 2.22 | 1.54 | 3.31 | 2.94 | 3.53 |

*Note: Gross profitablility, residual CAPM volatility, and systematic volatility are used as target variables in the optimization.*

*Source: MSCI ESG Research LLC. Data from December 2006 to December 2019 for the MSCI World Index.*

issues and their respective weights are readjusted on an annual basis, through a process that combines quantitative assessment of industry exposures to emerging issues and wide consultation with investment practitioners.[8]

Using this process, weights have varied over time across sectors. During our 13-year study period, there were over 2,000 permutations of E, S, and G weights. As of the end of 2019, the weight of the E pillar ranged from 5.8% for the communication services sector to 62.1% for utilities; the weight of the S pillar ranged from 16.3% for energy to 59.8% for the financials sector. Over the 13-year study period, the pillar weights averaged 30% for environmental key issues, 39% for social key issues and 31% for governance key issues. These weights showed significant variation over time. The average G pillar weight increased from an average of 19% in the first half of the sample period (2007–2012) to 25% in the second half (2013–2019), highlighting the increasing importance of governance issues over time.

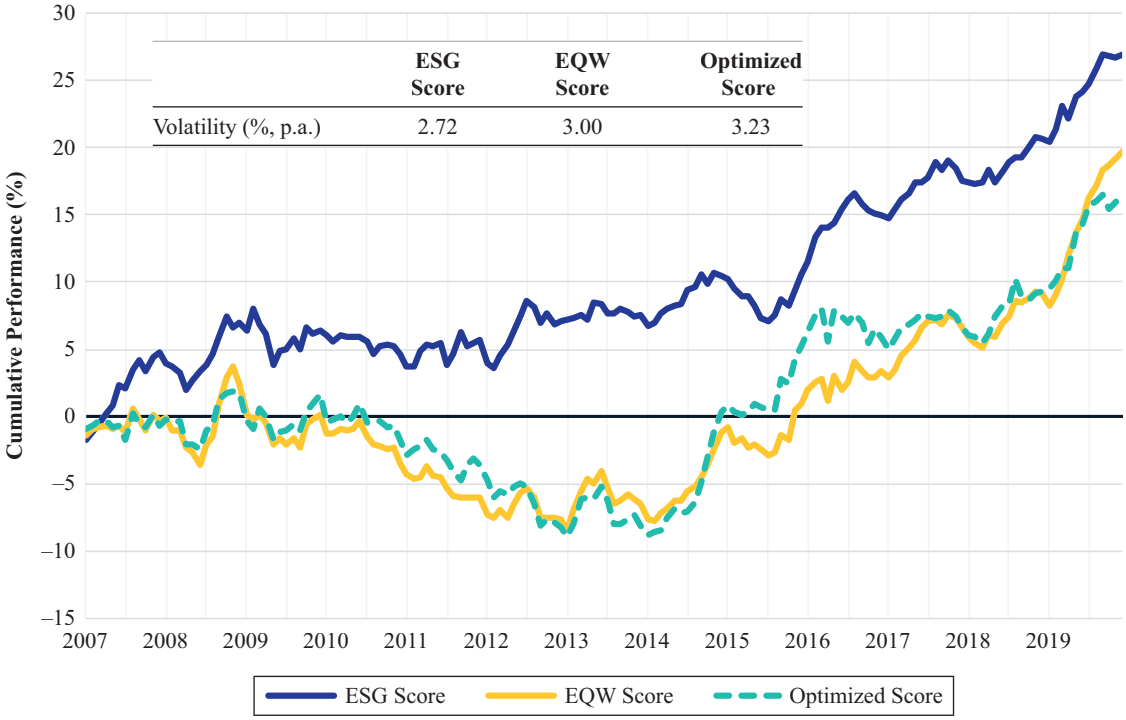
Overall, this finding suggests that backward optimization may be suboptimal over time, for two reasons. First, different E, S, and G risks have varying time horizons. For example, there are event-driven risks, such as those of ethics or fraud incidents, that can affect financial performance over relatively short periods of time. In contrast, other types of risk, such as poor talent management, may more gradually erode the stock price, only over longer periods of time. Therefore, optimizing performance over a limited period may not deliver optimal performance results over a longer horizon.

Second, the significance of ESG risks within any ESG-rating methodology may change over time due to shifts in the environment (e.g., climate change) or society. Therefore, an optimization approach that aims to maximize the same financial variables over longer periods of time may not lead to optimal results.

In essence, our results suggest that using a naïve approach of combining E, S, and G scores (such as with equal weighting) could have introduced noise and lessened the financial significance of an ESG score. Using backward optimization, on the other hand, may have helped ESG-rating providers understand how sensitive their rating model was to changes in the weighting scheme—and may have provided insights for fine-tuning their rating model. However, our research raises a cautionary flag for using a mechanistic backward-optimization approach as part of a scoring aggregation methodology.

[8] ESG Ratings Methodology. See also "2020 ESG Ratings Model Consultation." (Client access only.) MSCI ESG Research's annual consultation solicits feedback from its institutional-investor clients on proposals to enhance the ratings methodology and recalibrate industry-specific inputs.

## EXHIBIT 6
**Performance of Q5–Q1 Portfolios (in USD)**




*Note: Comparison of MSCI ESG industry-adjusted scores, equal-pillar-weighted scores, and optimized ESG scores.*
*Source: MSCI ESG Research LLC. Data from December 2006 to December 2019 for the MSCI World Index.*

## CONCLUSION

ESG strategies typically use inputs that score or rate companies on their ESG characteristics. But what indicators support that approach, and what role do the weights applied to these indicators play? We used the underlying pillar scores of the MSCI ESG rating to test the effect of ESG scores in two ways: how they related to financial characteristics of firms via three economic transmission channels, as well as how they correlated to long-term stock performance over 13 years.

Within our analysis of economic transmission channels, the top quintiles showed higher profitability and lower levels of idiosyncratic and stock-specific risk than the bottom quintiles for the majority of ESG pillar scores. Governance indicators showed the strongest significance at a pillar-score level.

We tested how alternative approaches to combining these pillar scores might have related to companies' financial characteristics and their long-term stock performance. We looked at both equal-weighting and backward-optimization approaches. They both showed slightly more significance than the MSCI ESG score.

However, when using financial-performance measures to optimize or fine-tune the weighting scheme for E, S, and G scores within the aggregated ESG rating, one runs the risk of data mining. Therefore, researchers may consider limiting the number of parameters used in the optimization to mitigate the risk of overfitting historical data.

In our study, we used a simple optimization of the relative weights of E, S, and G in the total ESG score. We found that the optimization increased the financial significance of the alternative ESG-rating model for financial performance and risk. However, the optimized scores failed to produce better long-term stock-price performance in our study period.

This finding illustrates one of the challenges of ESG-rating methodologies: The key risks that can drive financial results are not static but may change over time.

An analytical optimization based solely on historical data, and a static target function, may in practice be simplistic and too backward-looking. Nevertheless, different weighting schemes can be used to fine-tune ESG-rating methodologies, enhancing their forward-looking assessment of ESG risks and how such risks may be reflected in the rating model.

## REFERENCES


Eccles, R., I. Ioannou, and G. Serafeim. 2014. "The Impact of Corporate Sustainability on Organizational Processes and Performance." *Management Science* 60 (11): 2835–2857.

El Ghoul, S., O. Guedhami, C. Kwok, and R. Mishra. 2011. "Does Corporate Social Responsibility Affect the Cost of Capital?" *Journal of Banking & Finance* 35 (9): 2388–2406.

Fatemi, A., I. Fooladi, and H. Tehranian. 2015. "Valuation Effects of Corporate Social Responsibility." *Journal of Banking & Finance* 59 (C): 182–192.

Giese, G., L. E., Lee, D. Melas, Z. Nagy, and L. Nishikawa. 2019a. "Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk and Performance." *The Journal of Portfolio Management* 45 (5): 69–83.

——. 2019b. "Performance and Risk Analysis of Index-Based ESG Portfolios." *The Journal of Index Investing* 9 (4): 46–57.

Gregory, A., R. Tharyan, and J. Whittaker. 2014. "Corporate Social Responsibility and Firm Value: Disaggregating the Effects on Cash Flow, Risk and Growth." *Journal of Business Ethics* 124 (4): 633–657.

Lodh, A. 2020. "ESG and the Cost of Capital." MSCI Blog, February 25, 2020. https://www.msci.com/www/blog-posts/esg-and-the-cost-of-capital/01726513589.

MSCI ESG Research. 2019. "MSCI ESG Ratings Methodology." Available at https://www.msci.com.





*To order reprints of this article, please contact David Rowe at d.rowe@pageantmedia.com or 646-891-2157.*


## ADDITIONAL READING

### Foundations of ESG Investing: How ESG Affects Equity Valuation, Risk, and Performance


Guido Giese, Linda-Eling Lee, Dimitris Melas, Zoltán Nagy, and Laura Nishikawa



*The Journal of Portfolio Management*
**https://jpm.pm-research.com/content/45/5/69**



**ABSTRACT:** *Many studies have focused on the relationship between companies with strong environmental, social, and governance (ESG) characteristics and corporate financial performance. However, these have often struggled to show that positive correlations—when produced—can in fact explain the behavior. The authors of this article provide a link between ESG information and the valuation and performance of companies, by examining three transmission channels*

*within a standard discounted cash flow model—which they call the cash-flow channel, the idiosyncratic risk channel, and the valuation channel. They tested each of these transmission channels using MSCI ESG Ratings data and financial variables. This showed that companies' ESG information was transmitted to their valuation and performance, both through their systematic risk profile (lower costs of capital and higher valuations) and their idiosyncratic risk profile (higher profitability and lower exposures to tail risk). The research suggests that changes in a company's ESG characteristics may be a useful financial indicator. ESG ratings may also be suitable for integration into policy benchmarks and financial analyses.*

### Performance and Risk Analysis of Index-Based ESG Portfolios

Guido Giese, Linda-Eling Lee, Dimitris Melas, Zoltán Nagy, and Laura Nishikawa

*The Journal of Index Investing*
**https://jii.pm-research.com/content/9/4/46**

**ABSTRACT:** *There has been a wide range of research in academia and the asset management industry about the financial benefits of ESG investing. However, the question of how to achieve consistency when integrating ESG has not obtained the same level of attention. As a result, ESG integration currently is often applied inconsistently and incompletely across asset owners' portfolios. The authors of this article focus on how asset owners can implement ESG integration through index-based allocations to portfolios that seek to replicate ESG indexes. Index-based approaches offer consistency, transparency, and replicability and are generally cost-effective. Over a seven-year study period, global and regional versions of the MSCI ESG Leaders Indexes (as proxies for regional allocations) resulted in significant variations in their respective ESG profiles and performance, but in all instances, there was a clear reduction in all key risk measures.*